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A Joint Program for Agriculture and Resources Inventory Surveys Through Aerospace Remote Sensing

Supporting Research

February 1980

TECHNICAL REPORT

LABEL IDENTIFICATION FROM STATISTICAL TABULATION (LIST) TEMPORAL EXTENDABILITY STUDY

T. B. Dennis

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16. Abstract

In dot labeling, the Label Identification from Statistical Tabulation (LIST) approach is to apply a discriminant procedure to each dot which is a candidate for labeling. To use this technology operationally, a discriminant must be trained using ground-truth labels from a different year. Problems have been encountered when trying to temporally extend LIST discriminants from one year to the next. The purpose of this memorandum is to report the results of a study of these problems.

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TECHNICAL REPORT

LABEL IDENTIFICATION FROM STATISTICAL TABULATION (LIST) TEMPORAL EXTENDABILITY STUDY

Job Order 73-302

This report describes Classification activities of the Supporting Research project of the AgRISTARS program.

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LOCKHEED ENGINEERING AND MANAGEMENT SERVICES COMPANY, INC.
Under Contract NASA 9-15800

For

Earth Observations Division
Space and Life Sciences Directorate
NATIONAL AERONAUTICS AND SPACE ADMINISTRATION
LYNDON B. JOHNSON SPACE CENTER
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PREFACE

The analysis presented in this report was performed by Lockheed Engineering and Management Services Company, Inc., under Contract NAS 9-15800, for the Earth Observations Division, Space and Life Sciences Directorate, at the Lyndon B. Johnson Space Center, National Aeronautics and Space Administration.

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1. BACKGROUND

Label Identification from Statistical Tabulation (LIST) is a semiautomated labeling procedure developed to integrate analyst-interpreter (AI) information and Land Satellite (Landsat) spectral data into a consistent technology for labeling picture elements (pixels) as either small grain or nonsmall grain. This procedure is designed for labeling grains through the use of postharvest Landsat data. It requires four acquisitions of satellite data during the growing season. In this procedure, the AI is required to answer questions about the segment and the individual pixels which relate to simple properties that discriminate small-grain pixels from other pixels. The AI responses to these questions are combined with spectral, agricultural, and meteorological data to obtain keys or features for discrimination. These keys are statistically weighted using blind-site ground-truth data to develop a discriminant function which is applied to a large set of segments.

Personnel of Lockheed Electronics Company, Inc., began work on the LIST procedure in 1977 in support of the Large Area Crop Inventory Experiment (LACIE) within the Earth Observations Division (EOD) at the National Aeronautics and Space Administration (NASA), Lyndon B. Johnson Space Center (JSC). The preliminary development was analyzed by Pore (ref. 1). From this analysis, a semiautomated operational LIST was developed by Abotteen and Pore (ref. 2) and tested on blind sites in both Kansas and North Dakota (ref. 3). Improvements in the green number and brightness keys used in LIST were made by Dennis and Pore (ref. 4), and the resulting discriminant was tested on Large Area Crop Inventory Experiment (LACIE) Phase III Kansas data (ref. 5). In addition, alternative spectral keys were studied by Dennis and Pore (ref. 6) for possible inclusion in LIST.

The Kansas test (ref. 5) demonstrated that LIST could be a useful tool in identifying problem pixels in the labeling process. In view of these positive results, a decision was made to transfer the LIST technology to the NASA/JSC/EOD Crop Applications Branch for testing in the fiscal year (FY) 1980 pilot test under the ongoing Agriculture and Resources Inventory Surveys Through

Remote Sensing (AgRISTARS) program. To transfer a fully developed discriminant for use on 1979 spring-wheat data, it was necessary to demonstrate the year-to-year and geographic extendability of LIST. To show this, North Dakota data from Phase III (1977) and North Dakota, South Dakota, and Minnesota data from the 1978 Transition Year (TY) were analyzed. The analysis of this data is the subject of this report.

2. THE PROBLEM

To demonstrate both the temporal and geographic extendability of the LIST procedure before proceding to the FY 1980 pilot test, the decision was made to train the LIST discriminant using all available Phase III North Dakota segments. A test was then made to determine the accuracy of the discriminant on the TY North Dakota segments for an indication of temporal extendability. An additional test was performed on the TY Minnesota and South Dakota segments for an indication of temporal and geographic extendability. A complete list of the blind-site acquisitions used is shown in table 2-1.

The training accuracy observed in the Phase III North Dakota segments was comparable to the accuracy obtained in the Kansas test of LIST (ref. 5). These training results are presented in table 2-2, along with comparative AI labeling accuracy. When the initial results of applying LIST to the TY data were presented to the AI's for resolution of the discrepancies, it was determined that the large number of discrepancies involved would prevent LIST from being a useful tool for identifying problem pixels.

Test accuracies were obtained for the TY data and are presented in table 2-3. Note that the accuracy was not improved by considering only the temporal extendability to the North Dakota TY blind sites. The randomness of these results [i.e., a LIST probability of correct classification (PCC) close to 50 percent, the high average number of disagreements between LIST and the AI, and the lack of improvement in PCC over AI accuracy when LIST and the AI agreed] seemed to indicate that a problem existed in the TY data. The Phase III raw test data had been merged at the Purdue University for Applications of Remote Sensing (LARS) from the existing data tapes at that facility. The four channel data tapes for the TY segments had not been transferred to LARS, and, therefore, it was decided to merge the TY data on the Earth Resources Interactive Processing System (ERIPS) and transfer the merged 16-channel data to LARS for LIST processing. However, the ERIPS merge was shown not to be random data. Thus, to exclude the possibility of having improperly merged the TY data, a new discriminant was trained using that data. The high

TABLE 2-1.- BLIND SITES, LOCATION OF BLIND SITES, AND ACQUISITIONS

Segment	County	Acquisitions
Phase III, North Dakota		
1602	Montrail	77125, 77143, 77179, 77198
1606	Ward	77125, 77143, 77197, 77250
1616	Cavalier	77123, 77141, 77159, 77230
1619	Grand Forks	77122, 77140, 77158, 77175
1622	Ramsey	77141, 77159, 77176, 77230
1625	Dunn	77125, 77179, 77197, 77233
1635	Sheridan	77105, 77123, 77159, 77195
1640	Barnes	77121, 77140, 77175, 77211
1648	Bowman	77107, 77125, 77143, 77179
1652	Stark	77125, 77179, 77197, 77233
1899	Walsh	77122, 77157, 77175, 77193
1902	McKenzie	77107, 77125, 77144, 77197
1903	Mercer	77125, 77179, 77197, 77233
1913	Hettinger	77125, 77161, 77179, 77215
TY, North Dakota		
1394	Burke	78120, 78174, 78228, 78264
1457	Ward	78174, 78228, 78246, 78264
1461	Pierce	78137, 78190, 78217, 78236
1472	Barnes	78117, 78135, 78216, 78243
1473	Cass	78116, 78197, 78207, 78251
1584	Pembina	78117, 78198, 78216, 78243
1602	Montrial	78174, 78211, 78228, 78264
1612	McHenry	78137, 78155, 78199, 78236
1619	Grand Forks	78135, 78207, 78243, 78252
1636	Stutsman	78136, 78154, 78217, 78243
1650	Hettinger	78156, 78209, 78218, 78246
1656	Morton	78137, 78155, 78209, 78263
1658	Dickey	78117, 78135, 78207, 78252
1909	Kidder	78136, 78154, 78208, 78217
1918	Grant	78137, 78209, 78236, 78263
TY, South Dakota		
1668	Perkins	78156, 78174, 78228, 78264
1676	Bruce	78135, 78207, 78224, 78234
1755	Jerauld	78117, 78153, 78197, 78225
1784	Minnehaha	78134, 78169, 78196, 78223
TY, Minnesota		
1380	Rockwood	78115, 78169, 78204, 78222
1518	Roseau	78135, 78188, 78224, 78243
1566	Grant	78133, 78169, 78196, 78232
1825	Norman	78133, 78169, 78196, 78232
1842	Yellow Medicine	78133, 78205, 78223, 78241

TABLE 2-2.- TRAINING RESULTS FOR PHASE III NORTH DAKOTA SEGMENTS

(a) Distribution of LIST labels

Ground-truth label	LIST label		
	Small grains	Nonsmall grains	Obvious nonagriculture
Small grains	534	167	13
Nonsmall grains	143	669	496

Statistics:
- PCC = 84.07%
- Omission rate = 25.21%
- Commission rate = 10.93%
- Bias = -1.8%
- Average PCC across segments = 84.31%
- Standard deviation of PCC = 4.69%
- PCC, given LIST and AI agree = 88.03%
- PCC of LIST on disagreements = 40.97%

(b) Distribution of AI labels

Ground-truth label	AI label		
	Small grains	Nonsmall grains	Obvious nonagriculture
Small grains	370	330	13
Nonsmall grains	63	751	496

Statistics:
- PCC = 80.00%
- Omission rate = 48.11%
- Commission rate = 4.66%
- Bias = -14.0%
- Average PCC across segments = 80.46%
- Standard deviation of PCC = 9.75%

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TABLE 2-3.- INITIAL RESULTS FROM CLASSIFYING TY DATA WITH THE PHASE III DISCRIMINANT

(a) Distribution of LIST labels for 19 TY sites in North Dakota, South Dakota, and Minnesota

Ground-truth label	LIST label		
	Small grains	Nonsmall grains	Obvious nonagriculture
Small grains	339	612	12
Nonsmall grains	660	1005	246

Statistics:
- PCC = 55.32%
- Omission rate = 64.00%
- Commission rate = 34.54%
- Bias = +1.7%
- Average PCC across segments = 57.13%
- Standard deviation of PCC = 20.14%
- PCC, given LIST and AI agree = 81.07%
- PCC of LIST on disagreements = 18.79%

(b) Distribution of LIST labels for 14 North Dakota TY blind sites

Ground-truth label	LIST label		
	Small grains	Nonsmall grains	Obvious nonagriculture
Small grains	286	512	9
Nonsmall grains	406	797	110

Statistics:
- PCC = 52.26%
- Omission rate = 63.44%
- Commission rate = 30.97%
- Bias = -5.0%

training accuracy, shown in table 2-4, ruled out the possibility that raw data problems created the random effect shown in table 2-3. A correlation was computed between the two discriminant vectors.

This correlation showed the vectors to be nearly orthogonal, which indicates that the decision boundary between grains and nongrains changed drastically from Phase III to TY. Clearly, there is a real problem in extending the LIST discriminant from one year to the next, although the LIST questions still appear to discriminate small-grain pixels from other pixels. Some possible causes of this poor temporal extendability are discussed in the next section.

TABLE 2-4.- TRAINING RESULTS FOR TY NORTH DAKOTA, SOUTH DAKOTA, AND MINNESOTA DATA

(a) Distribution of LIST labels for 15 North Dakota blind sites

Ground-truth label	LIST label		
	Small grains	Nonsmall grains	Obvious nonagriculture
Small grains	502	323	10
Nonsmall grains	128	1230	196

Statistics:
- PCC = 80.70%
- Omission rate = 39.80%
- Commission rate = 8.20%
- Bias = -8.5%
- Average PCC across segments = 79.23%
- Standard deviation of PCC = 11.22%
- PCC, given LIST and AI agree = 83.6%
- PCC of LIST on Disagreements = 54.1%

(b) Distribution of LIST labels for 21 North Dakota, South Dakota, and Minnesota blind sites

Ground-truth label	LIST label		
	Small grains	Nonsmall grains	Obvious nonagriculture
Small grains	583	418	14
Nonsmall grains	127	1788	322

Statistics:
- PCC = 82.81%
- Omission rate = 42.56%
- Commission rate = 5.68%
- Bias = -9.4%
- Average PCC across segments = 84.27%
- Standard deviation of PCC = 11.5%

3. POSSIBLE CAUSES OF POOR TEMPORAL EXTENDABILITY

Four factors could have caused or contributed to the lack of temporal extendability discussed in the previous section. Briefly, these factors are as follows:

a. Inherent difference in the separability of the data from one year to the next

b. A need for temporally current keys

c. Insufficient representation of AI in the Phase III test

d. Insufficient training data

The first factor relates to changes in the separability of the data from Phase III to TY. In J. Clinton's study on Labeling characterization (ref. 7), the labeling accuracy for North Dakota was shown to be 85.85 percent for Phase III segments and 83.94 percent for the TY segments. This indicates that, to a small degree, the Phase III data are naturally more separable. Thus, more latitude is available in the placement of the discriminant boundaries in the Phase III data than in the TY data. Furthermore, when applied to the Phase III data, the TY discriminant yields results which are no longer random, though they are marginal at best (see table 3-1).

The second factor relates to the way in which spectral data keys are developed and used in LIST. For this study, the four observations of greenness and brightness for a given pixel were compared to an expected trajectory of small grains for the observed growth stages reported for the segment. This expected trajectory was developed using Phase III North Dakota data. Thus, Phase III training may not apply to TY small-grain data if, as a whole, the latter data follow a different trajectory. Thus, a set of temporally current trajectories or temporally current spectral keys may need to be developed.

The third factor involves a possible imbalance of AI keys in much the same way that the second factor involves such an imbalance of spectral keys.

TABLE 3-1.- RESULTS FROM CLASSIFYING PHASE III DATA WITH THE TY DISCRIMINANT

[Distribution of LIST labels]

Ground-truth label	LIST label		
	Small grains	Nonsmall grains	Obvious nonagriculture
Small grains	451	250	13
Nonsmall grains	385	427	496

Statistics:
- PCC = 67.99%
- Omission rate = 36.83%
- Commission rate = 29.43%
- Bias = +6.0%
- Average PCC across segments = 67.76%
- Standard deviation of PCC = 21.11%
- PCC, given LIST and AI agree = 83.18%
- PCC of LIST on disagreements = 24.25%

The problem is that only two AI's were available for answering the LIST questions for Phase III data, while for the TY data, 16 AI's provided these responses. Two AI's may not provide a broad enough spectrum of responses to obtain a proper balance of those features in the final discriminant.

The final factor relates to the size of the set of training pixels used for the Phase III data. First of all, there were only 14 segments available for training purposes in Phase III. Second, the two AI's may have been too liberal in assigning pixels the label D, which was intended remove the obviously nonagricultural pixels. In Phase III, 25.07 percent of the total pixels available for training were removed because of this designation. By comparison, only 10.25 percent of the TY pixels were put in this category. Consequently, the effects of this factor and the first factor are difficult, if not impossible, to measure.

In the next section, a method of temporally updating spectral keys is discussed and applied to the data. Various subsets of the LIST keys are examined in the context of their individual contribution to the temporal signature extension problem.

4. ANALYSIS OF KEYS

The first attempt to explain the problem of temporal signature extension was to show the importance of using temporally current spectral keys. Figures 4-1 and 4-2 are graphs showing the expected trajectory (given as a mean ±1 standard deviation) of greenness and brightness as a function of the observed Robertson biostage. These trajectories were obtained using the available ground-truth small-grain pixels from the Phase III North Dakota segments. They are used to transform the raw spectral data into a new set of LIST keys. The basic theory involved is that the variance of the spectral transformation of a pixel from this trajectory is a measure of the probability of that pixel not being a small-grain pixel. However, if meteorological conditions cause these trajectories to change from one year to the next, the use of the previous year's trajectories may induce variance which has no relation to the true class of the pixels involved. It was believed that this problem could be avoided by using the following operationally feasible method in updating these trajectories:

a. Train the discriminant as before, using one year's worth of data to build the trajectories and find the weights of the discriminants

b. Before classifying the next year's data, recompute the trajectories by using all the AI-labeled small-grain pixels for that year

Since AI labels were already provided as part of the AI responses for LIST, no new resources were needed to test this concept. A question arises, however, in the validity of this approach. Namely, does the AI induce significant errors in the trajectories by being conservative in his labeling. Figures 4-3 through 4-6 are graphs of the TY greenness and brightness trajectories computed using ground-truth and AI labels, alternately. These trajectories do not appear to be significantly different. Figures 4-7 and 4-8 are greenness and brightness trajectories computed using Phase III AI labels. These trajectories show significant bias when compared to the ground-truth trajectories for that year (figures 4-1 and 4-2). Therefore, the indications are that this method of updating keys is feasible when extending from Phase III to TY, although it might not be reliable if the two data sets were reversed.

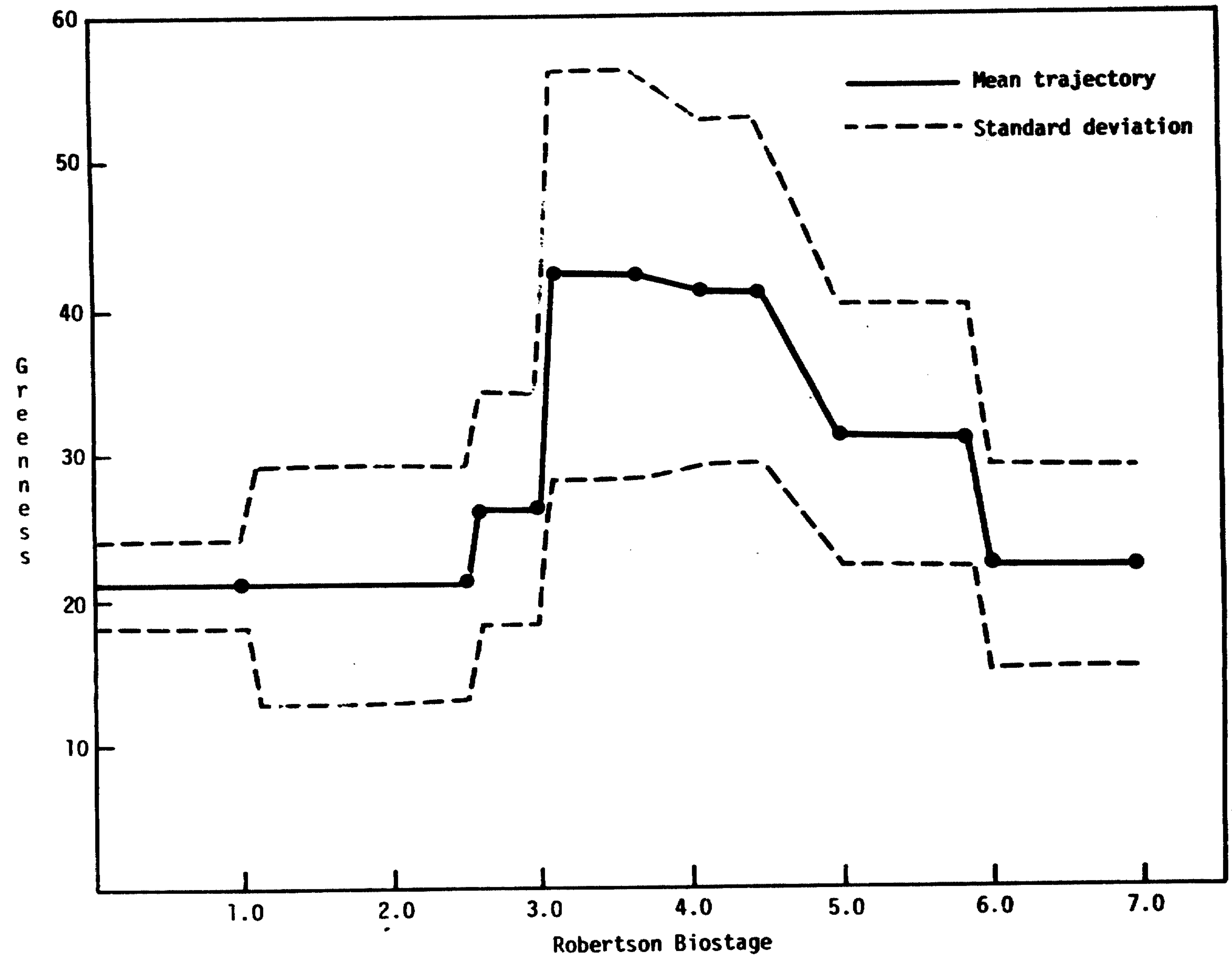

Figure 4-1.– Phase III greenness key generated from the ground-truth labels for North Dakota segments.

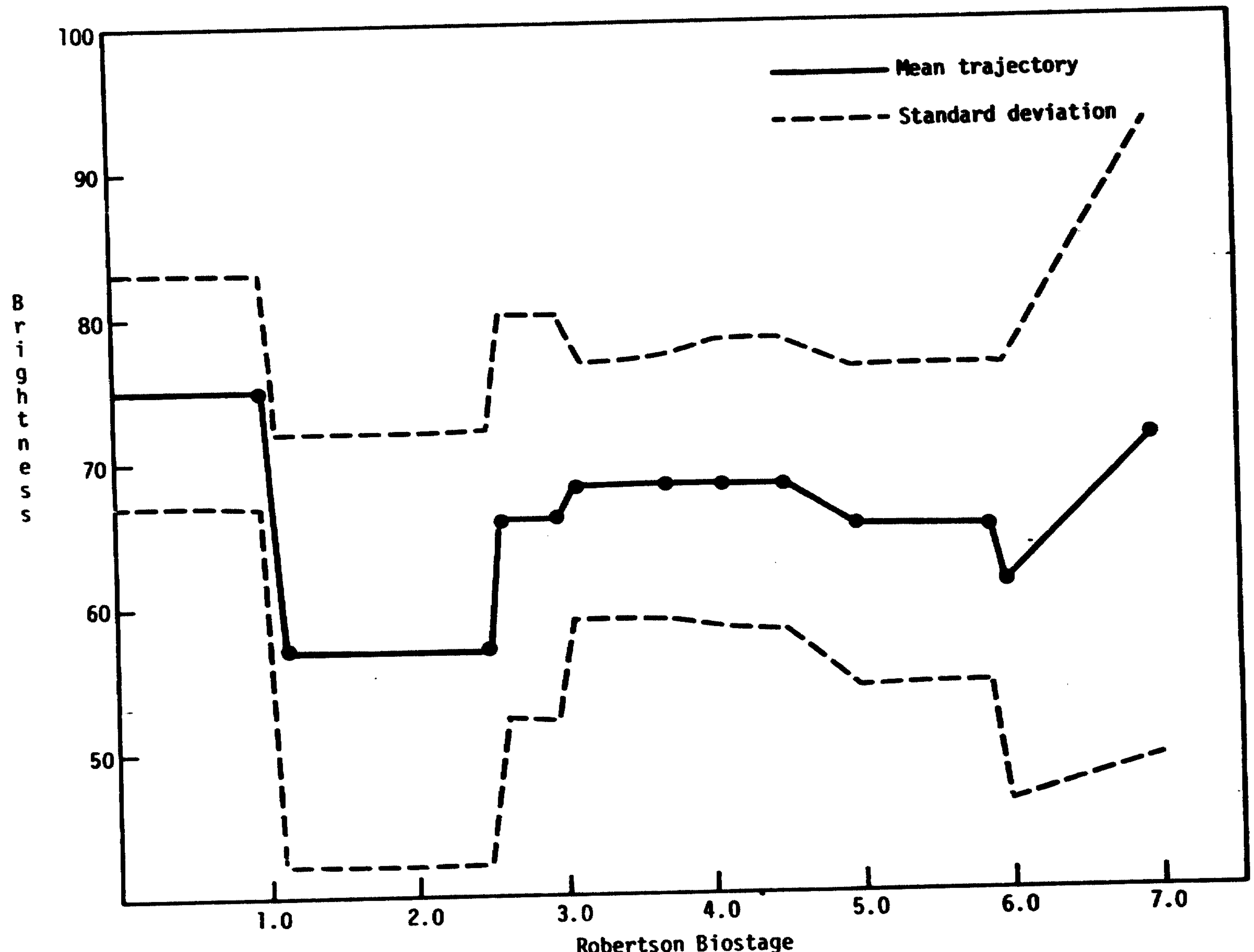

Figure 4-2.– Phase III brightness key generated from the ground-truth labels for North Dakota segments.

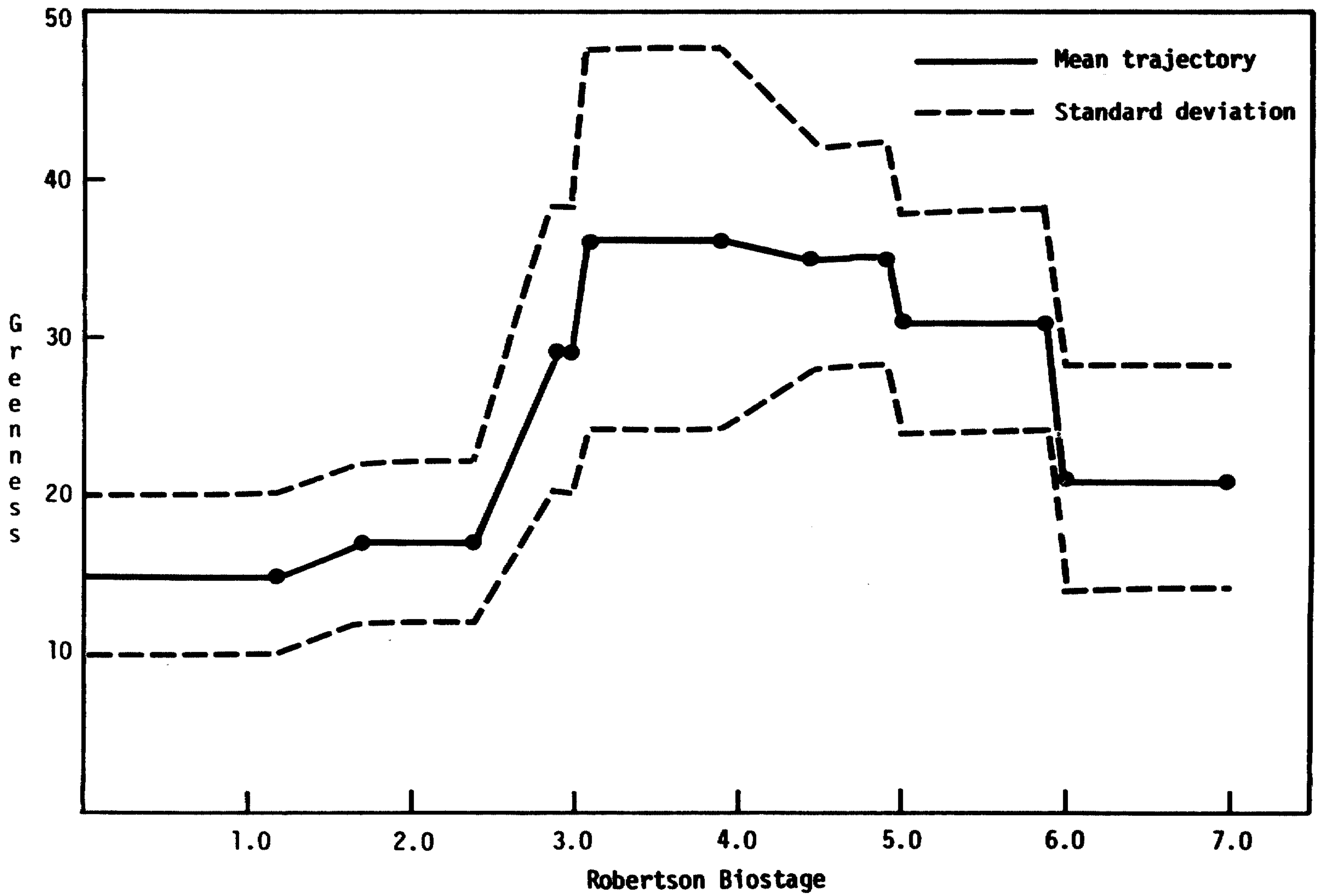

Figure 4-3.— TY greenness key generated from the ground-truth labels.

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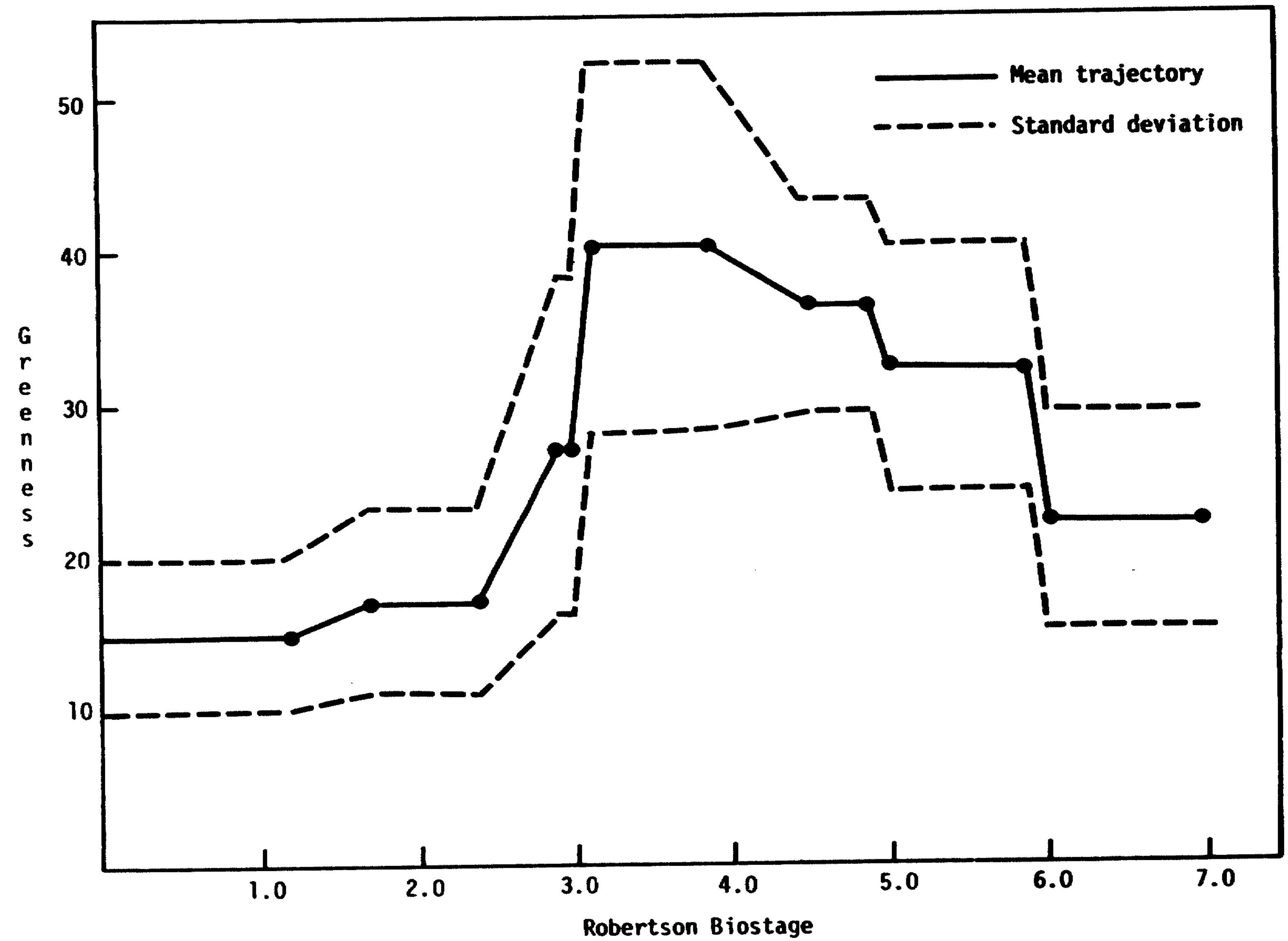

Figure 4-4.— TY greenness key generated from the AI labels.

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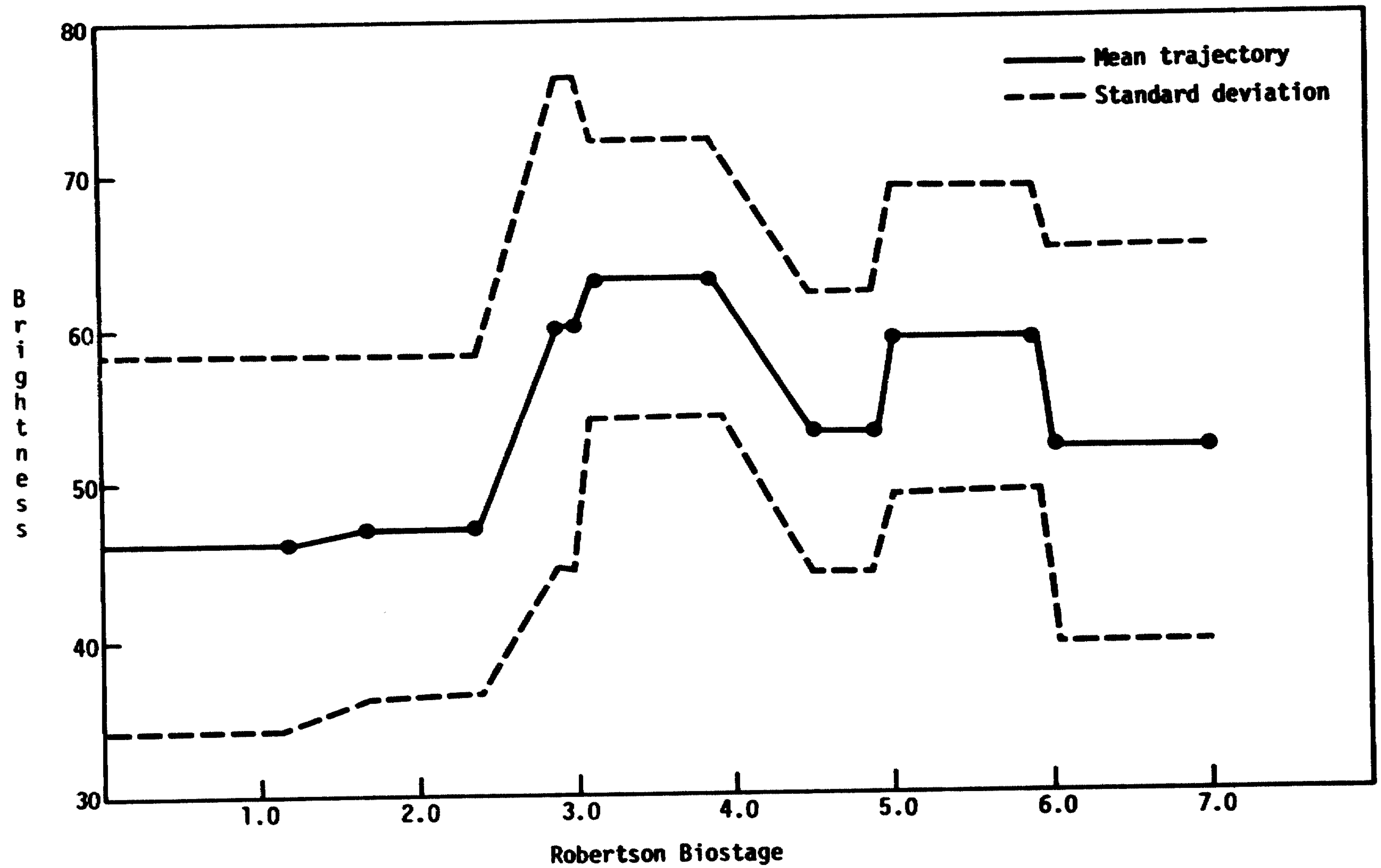

Figure 4-5.— TY brightness key generated from the ground-truth labels.

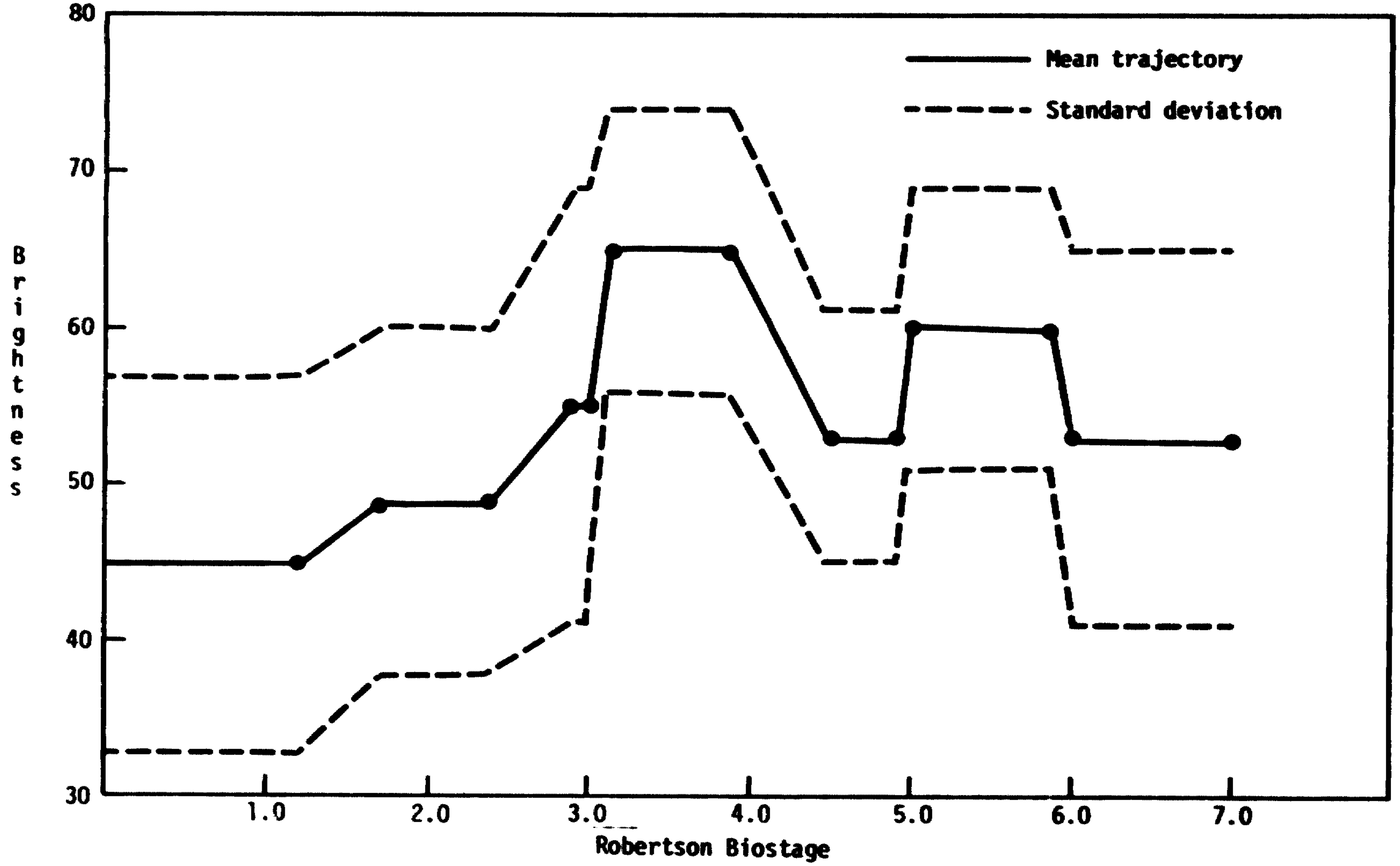

Figure 4-6.— TY brightness key generated from the AI labels.

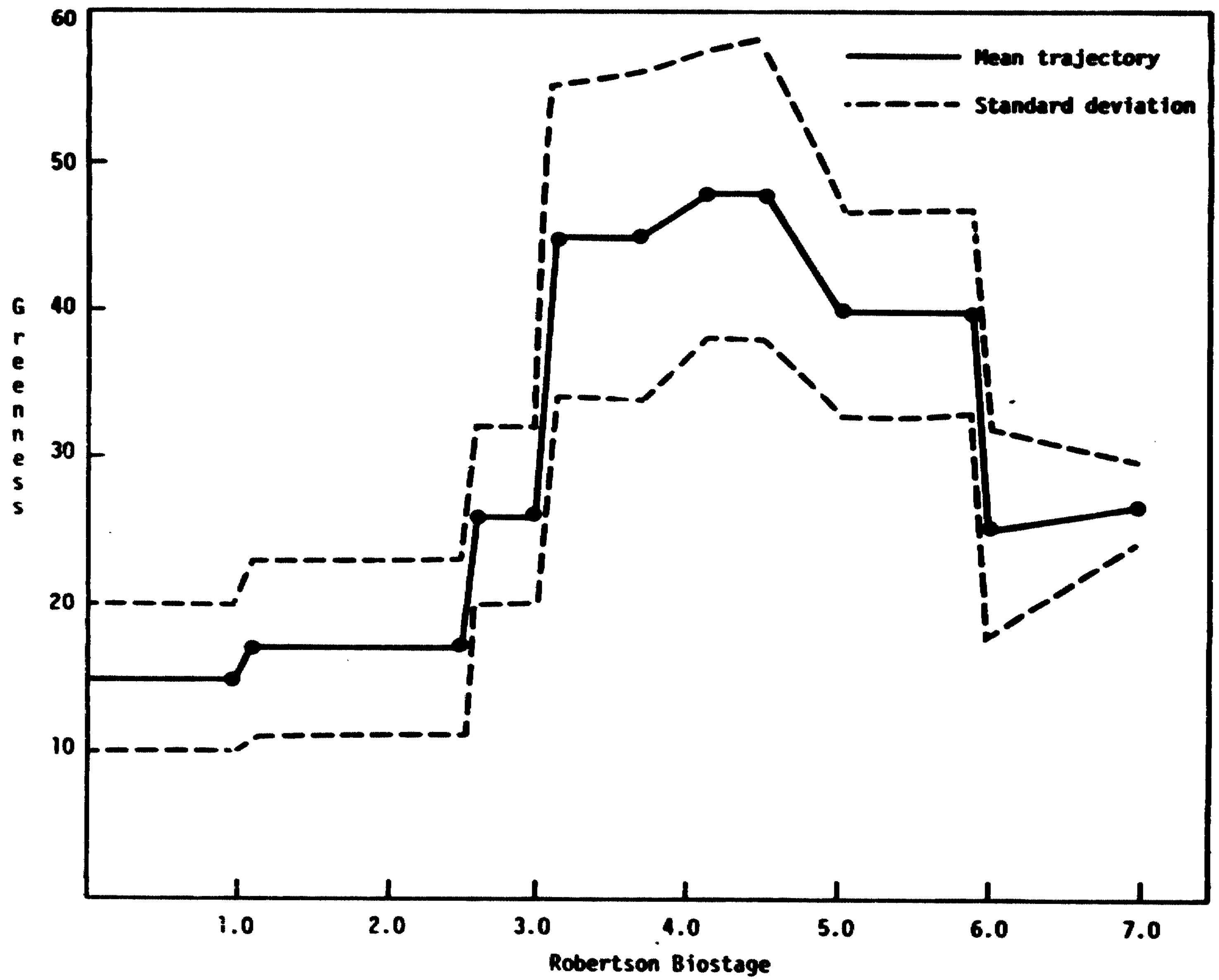

Figure 4-7.– Phase III greenness key generated from the AI labels.

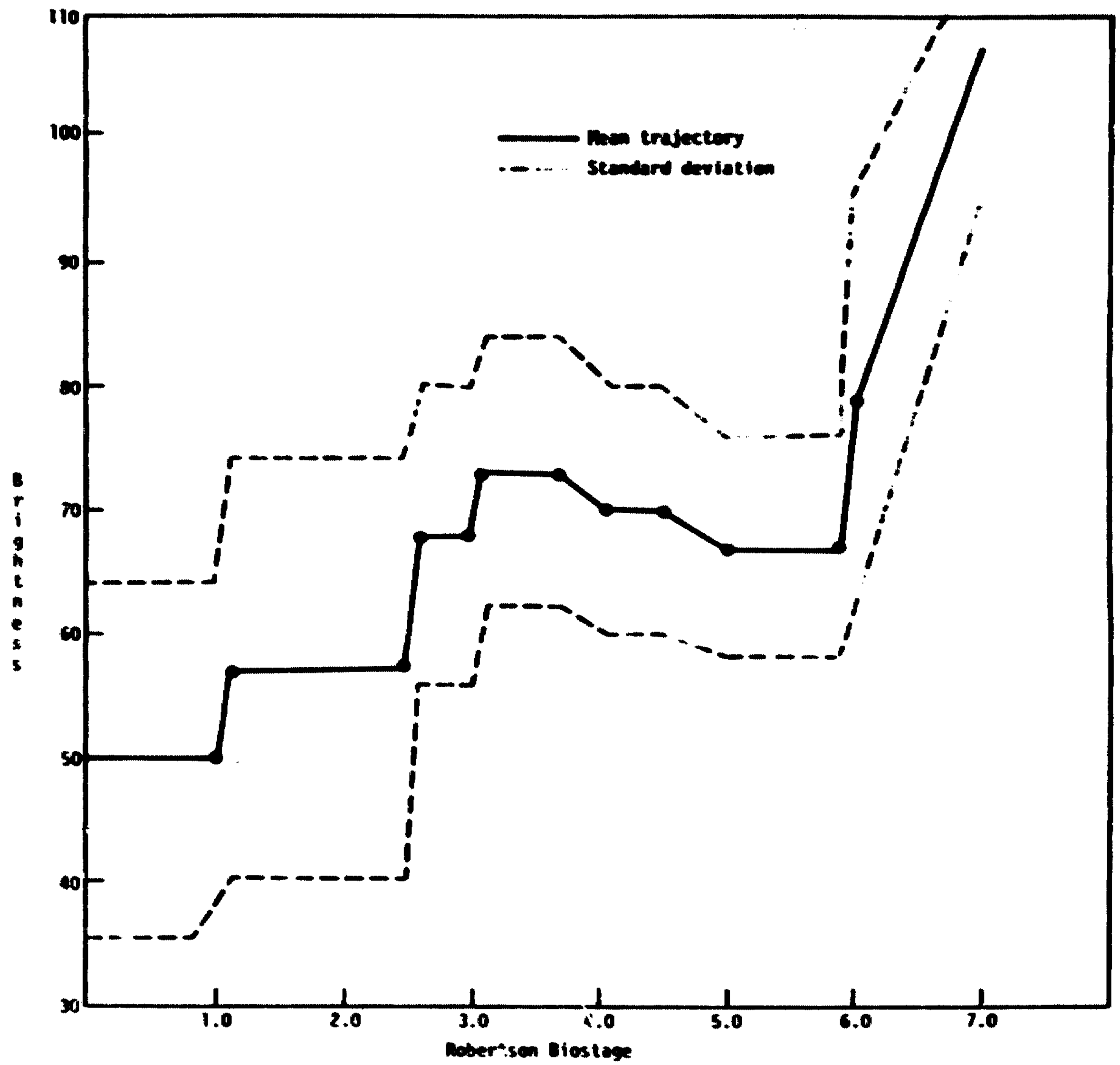

Figure 4-8.— Phase III brightness key generated from the AI labels.

One possible interpretation is that the bias noted in the Phase III AI trajectories is related to the third factor: only two AI's interpreted all of the Phase III segments. Thus, given a broad-based collection of AI's (such as the 16 AI's used in interpreting the TY data), the difference in the two methods of generating trajectories may not be noticeable. Table 4-1 shows that using temporally current trajectories does improve the temporal extendability, although not significantly. However, the use of temporally current keys in approaching the temporal extendability problem is not considered significant. It was decided, therefore, that in testing subsets of the keys for extendability, the ground-truth trajectories for Phase III would be used with the Phase III data and the AI-generated TY trajectories would be used with the TY data.

With the contribution of temporally current trajectories thus removed from the problem, the next most obvious difference in the spectral keys was in the change in the brightness trajectory from Phase III to TY. Table 4-2 shows the results obtained from removing the brightness keys and trying to extend from Phase III to TY using only the AI and greenness variables. These results reveal that brightness alone is not the cause of the poor extendability.

Tables 4-3, 4-4, and 4-5 show the extendability achieved using greenness/brightness keys, only greenness keys, and only AI keys, respectively. Table 4-6 shows training and independent test accuracies for those sets of keys which were applied to the TY data, reiterating that the problem involves only the temporal extandability of LIST.

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TABLE 4-1.- ACCURACY OF EXTENSION WITH UPDATED KEYS

(a) Distribution of LIST labels in classification of 24 TY segments with Phase III trained discriminant and updated keys

Ground-truth label	LIST label		
	Small grains	Nonsmall grains	Obvious nonagriculture
Small grains	321	739	14
Nonsmall grains	912	1593	359

Statistics:
- PCC = 57.72%
- Omission rate = 70.11%
- Commission rate = 31.84%
- Bias = +7.45%
- Average PCC across segments = 63%
- Standard deviation of PCC = 18.89%
- PCC, given LIST and AI agree = 84.55%
- PCC of LIST on disagreements = 18.8%

(b) Distribution of LIST labels in classification of 19 TY segments with Phase III weights without updated keys

Ground-truth label	LIST label		
	Small grains	Nonsmall grains	Obvious nonagriculture
Small grains	339	612	12
Nonsmall grains	660	1005	246

Statistics:
- PCC = 55.32%
- Omission rate = 64%
- Commission rate = 34.54%
- Bias = +1.7%
- Average PCC across segments = 57.13%
- Standard deviation of PCC = 20.14%
- PCC, given LIST and AI agree = 81.07%
- PCC of LIST on Disagreements = 18.79%

TABLE 4-2.- RESULTS OBTAINED BY REMOVING BRIGHTNESS KEYS

[Distribution of LIST labels for 24 TY blind sites, classified from Phase III training]

Ground-truth label	LIST label		
	Small grains	Nonsmall grains	Obvious nonagriculture
Small grains	465	595	14
Nonsmall grains	694	1511	359

Statistics:
- PCC = 64.18%
- Omission rate = 55.4%
- Commission rate = 27.07%
- Bias = +2.7%
- Average PCC across segments = 64.67%
- Standard deviation of PCC = 16.97%

TABLE 4-3.- RESULTS USING ONLY GREENNESS/BRIGHTNESS KEYS

Data used in training	Data set classified			
	Phase III		TY	
	Mean PCC	Standard deviation	Mean PCC	Standard deviation
Phase III	83.78	5.19	63.58	17.6
TY	70.26	17.27	82.42	10.26

TABLE 4-4.- RESULTS USING ONLY GREENNESS KEYS

Data used in training	Data set classified			
	Phase III		TY	
	Mean PCC	Standard deviation	Mean PCC	Standard deviation
Phase III	81.89	8.71	65.74	16.87
TY	72.62	20.18	77.24	12.8

TABLE 4-5.- EXTENDABILITY ACHIEVED USING ANALYST KEYS ONLY

(a) Results

Data used to train discriminant	Data classified					
	Phase III			TY		
	Overall PCC	Mean PCC	Standard deviation	Overall PCC	Mean PCC	Standard deviation
Phase III	73.7	73.86	15.69	59	59.15	23.76
TY 68.5	68.55	18.20	74	73.64	21.06	

(b) Probability of agreement of machine classified label and analyst label (classified using only AI keys)

Data used to train discriminant	Data classified	
	Phase III	TY
Phase III	0.567	0.637
TY	.672	.871

TABLE 4-6.- TRAINING AND TEST ACCURACY OF KEYS APPLIED TO THE TY DATA

Data set	Mean PCC	Standard deviation of the PCC
Greenness and brightness keys		
Training data	81.52	10.30
Test data	84.24	10.63
Greenness keys only		
Training data	75.87	12.62
Test data	79.97	13.56
AI keys only		
Training data	72.03	15.69
Test data	76.88	30.2

5. CONCLUSION

The most apparent contributors to the problem of poor temporal extension of LIST are the drastic changes in the brightness keys and an inadequate set of AI responses in Phase III. The brightness trajectories change drastically from Phase III to the TY. When classifying data, the inclusion of brightness channels with greenness channels increases accuracy within a year, but this combination decreases accuracy when used in classifying data from a year other than that of the training data. This indicates that brightness does not follow a trajectory which is consistently related to crop growth over several years.

Removing brightness channels from the discriminant, however, does not completely correct the lack of extendability. Note from tables 4-1 and 4-2 that removing brightness increases the accuracy of the extension from Phase III to TY from 57.72 percent to 64.18 percent. Note also that removal of the AI keys increases accuracy to 65.76 percent (table 4-4). Although the latter increase appears insignificant when compared to the first, note that removing only the AI keys increased accuracy to 63.58 percent (table 4-3).

Table 4-5 shows that it is the set of Phase III AI responses which is contributing most to the problem. Note that proper weighting of the responses explains 73.8 percent of the ground-truth labels but only 56.7 percent of the AI labels. By contrast, the TY responses which were weighted to explain the TY ground-truth labels faired equally well, explaining 73.6 percent of those labels and 87.1 percent of the AI labels.

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6. RECOMMENDATIONS

A satisfactory signature extension from Phase III to the TY has not been achieved with the current data and a meaningful subset of the current keys. It is possible, however, that with good AI responses for the Phase III data, some improvement would be manifested. On the other hand, it is possible that the questions asked of AI's cannot be answered reliably. In order to resolve these issues, it is recommended that multiple sets of responses to the LIST questions be collected for the Phase III North Dakota blind sites using a large number of AI's. It is also recommended that these responses be analyzed to determine (1) the consistency with which the LIST questions can be answered, (2) the relationship between the responses to the LIST questions and the AI label, and (3) the role of AI responses in the problem of temporal signature extension.

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